Renewable and Sustainable Energy Reviews 24 (2013) 111–121

Contents lists available at SciVerse ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

A review on sensorless techniques for sustainable reliablity and efficient variable frequency drives of induction motors

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ARTICLE INFO

Article history:
Received 18 August 2012
Received in revised form
8 March 2013
Accepted 15 March 2013
Available online 11 April 2013

Keywords:
Controlled drives
Induction motor
Speed estimation
Variable frequency drives
Vector control

ABSTRACT

Variable frequency drives (VFDs) can provide reliable dynamic systems and significant savings in energy usage and costs of the induction motors (IMs). Sensorless controlled IM drives have advantages in terms of efficiency enhancement and energy savings for critical applications such as electric vehicles, high performance machine tools, fans, compressors, etc. IM drives without having speed sensors or optical encoders mounted at the motor shaft are attractive because of their lower cost and higher reliability. When mechanical speed sensor is removed, the rotor speed information is estimated using the measured quantities of stator voltages and currents at the IM terminals. This paper highlights the sensorless techniques applied to the IM drives for sustainable reliability and energy savings. Overview on the IM mathematical model is briefly summarized to establish a physical basis for the sensorless schemes used. Further, the different types of IM-VFDs are presented in the paper. The main focus of this review is on the sensorless estimation techniques which are being applied to make IM-VFDs more effective during wide speed operations including very-high and very-low speed regions.

Contents

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1364-0321/$ - see front matter
http://dx.doi.org/10.1016/j.rser.2013.03.051

Nomenclature

A	system matrix
AC	alternating current
B	input matrix
BPF	band pass filter
DC	direct current
DTC	direct torque control
EKF	extended Kalman filter
FOC	field oriented control
IM	induction motor
i_s, i_r	stator and rotor current space vectors
KF	Kalman filter
LPF	low pass filter
L_s, L_r	stator and rotor self inductances
MRAS	model reference adaptive system
PWM	pulse-width modulation
R_s, R_r	stator and rotor resistances
SI	signal injection
SMO	sliding mode observer
SNR	signal to noise ratio
u	control-input vector
VC	vector control
VFD	variable frequency drives
v_s	stator voltage space vectors
ASD	adjustable speed drives
VSI	voltage source inverter
x	state space vector
σ	leakage coefficient, $\sigma = 1 - L_m^2/(L_s L_r)$
ω_r	rotor speed
τ_r	rotor time constant, $\tau_r = L_r/R_r$
L_σ	stator leakage, $L_\sigma = L_s - L_m^2/L_r$
ψ_s, $\overline{\psi}_r$	stator and rotor flux linkage space vectors

1. Introduction

Induction motors (IMs) dominate the world market (more than 85% of electrical motors) [1] with broad applications in industries, public services and household electrical appliances [2,3]. The popularity of IMs is mainly due to their low cost, ruggedness, high reliability, and minimum maintenance [4]. According to statistics on industrially developed nations, IMs contribute to more than 60% of total industrial electricity consumption [5]. Hence, employing high efficient and reliable IM drives would undoubtedly result in more economical drive systems that would significantly help in energy saving.

Induction motor drive systems, which are supplied directly from AC line power, have a great potential for energy saving, when they are operated at variable-speed by using variable frequency drives (VFDs). Energy consumption in centrifugal load applications vary according to the affinity laws [6], which means that torque is proportional to the square of speed, and power is proportional to the cube of speed. This change helps reduce high energy losses compared to fixed-speed controllers or throttling devices for a relatively small decrease in speed. For example, at 20% of speed a motor load needs only 50% of its full speed power [7].

VFDs can provide reliable dynamic systems and at the same time contribute significantly to the energy usage and costs of IM drives [3]. These drive systems are an excellent class of the general adjustable speed drives (ASDs) [3] because they permit fine-tuning processes while reducing costs for energy and motor maintenance [4,8]. In addition to energy savings, they can offer continuous speed control according to the specific requirements of the work being performed.

Accurate speed measurement is an essential requirement of VFDs for robust and high-precision control of IMs. The measurement of the IM rotor-speed can be performed by using mechanical and optical sensors, such as tachometers and optical encoders. Nevertheless, speed sensors increase hardware complexity, cost and size of the drive systems [9]. In addition, the reliability of the drive system is reduced, as well as regular maintenance for the encoder is required. The disadvantages of the mechanical speed sensors can be removed if the speed can be estimated from the terminal variables. Consequently, researches on techniques of speed estimation have received increasing attention in recent decades [9–11]. Speed estimation for VFDs is found especially in applications where the performance of the sensor tends to be poor

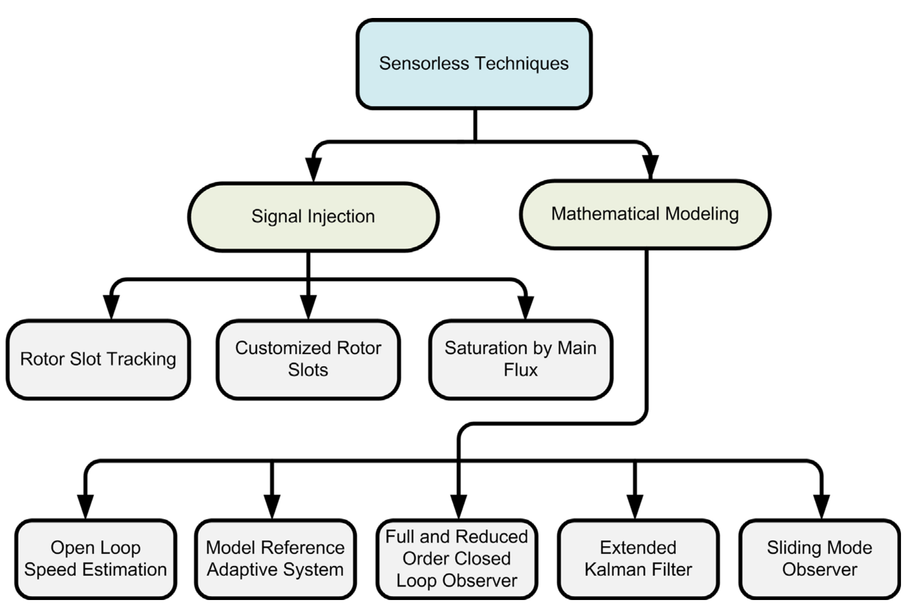

Fig. 1. Sensorless estimation techniques for induction motor.

or not suitable to be installed, such as in harsh environment. Two classes of sensorless techniques (see Fig. 1) have evolved over the past decades: estimation using mathematical model of the IM by employing space vectors equations, and estimation through signal injection via exploiting the anisotropy of the induction machine.

Model-based approaches are aimed to extract the speed information using voltage and current quantities obtained from the IM terminals. However, the performance of these model-based estimation techniques depends mostly on the accuracy of the parameters used for motor modeling [15]. It is well known that IM is a nonlinear time-varying system whereby its parameters vary with time and operating conditions, such as temperature, speed, and mechanical load. In particular, the rotor and stator resistances are the decisive parameters that have a significant influence on the estimation and control performance besides the variation in load torque. Consequently, the accuracy of the estimated speed using traditional model-based approaches is inadequate, unless fine parameter tuning is included in the estimation algorithm. Adaptation of parameters have become of great importance because any mismatch on the parameter values can cause not only speed error but also instability in the drive system.

Speed sensorless techniques based on signal injection offer good solution for parameter adaptation and sustainable zero speed, as well as long-term stability problems. This technique uses a carrier signal that is typically superimposed on the pulse-width modulated waveform of the power inverter. Two kinds of produced signals are normally used for estimating the rotor speed: negative-sequence carrier-signal and zero-sequence carrier-signal components [12]. However, there is a difficulty faced by signal processing due to demanded frequency tracking, poor signal-to-noise-ratio (SNR), and low spectral classification. These problems can be overcome with employing modern signal processing techniques, such as the wavelet processing algorithm [13].

This paper briefly reviews on the fundamentals and classifications of IM drive systems. The reviews on the recent development of estimation strategies for speed and parameter adaptations for high efficiency drive systems are also presented. The paper is aimed to provide essential guidelines and insights for future research and development on the sensorless energy saving or so-called variable frequency drive systems.

2. Mathematical modeling

The fundamental mathematical model of the IM in general reference frame is given by the following equations [14]:

$$v_s^g = R_s i_s^g + \frac{d\psi_s^g}{dt} + j\omega_g \psi_s^g \tag{1}$$

$$0 = R_r i_r^g + \frac{d\psi_r^g}{dt} + j(\omega_g - \omega_r)\psi_r^g \tag{2}$$

$$\psi_s^g = L_s i_s^g + L_m i_r^g \tag{3}$$

$$\psi_r^g = L_r i_r^g + L_m i_s^g \tag{4}$$

These equations are expressed in general reference frame denoted by the superscript ‘g’. Utilizing these equations, a number of techniques for sensorless speed control have been developed.

The state space model is a convenient way of representing the IM in developing the estimation and control algorithms, in solving the IM drive problems. Using this model form, any system described by high order differential equations can be modified to a set of first order differential equations. In addition, the internal behavior of the system can be easily determined together with the desired input and output. Moreover, it is usually an efficient form for computer simulation. The model for a nonlinear dynamic system of an IM in continuous time can be expressed in the state space form as given by

$$\underbrace{\begin{bmatrix} \dot{i}_{sd} \\ \dot{i}_{sq} \\ \dot{\psi}_{rd} \\ \dot{\psi}_{rq} \\ \dot{\omega}_r \end{bmatrix}}_{\dot{x}} = \underbrace{\begin{bmatrix} -\left(\frac{R_s}{L_\sigma} + \frac{L_m^2 R_r}{L_\sigma L_r^2}\right) & 0 & \frac{L_m R_r}{L_\sigma L_r^2} & \frac{\omega_r L_m}{L_\sigma L_r} & 0 \\ 0 & -\left(\frac{R_s}{L_\sigma} + \frac{L_m^2 R_r}{L_\sigma L_r^2}\right) & -\frac{\omega_r L_m}{L_\sigma L_r} & \frac{L_m R_r}{L_\sigma L_r^2} & 0 \\ \frac{R_r}{L_r} L_m & 0 & -\frac{R_r}{L_r} & -\omega_r & 0 \\ 0 & \frac{R_r}{L_r} L_m & \omega_r & -\frac{R_r}{L_r} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} i_{sd} \\ i_{sq} \\ \psi_{rd} \\ \psi_{rq} \\ \omega_r \end{bmatrix}}_{x} + \underbrace{\begin{bmatrix} 1/L_\sigma & 0 \\ 0 & 1/L_\sigma \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}}_{B} \underbrace{\begin{bmatrix} v_{sd} \\ v_{sq} \end{bmatrix}}_{u} \tag{5}$$

Eq. (5) is valid for both steady-state and transient-state conditions. The IM is a dynamic system due to the differential operations, a time-varying system due to the variations in load torque and other system parameters, such as temperature and frequency based variations of rotor and stator resistances, and a nonlinear system due to the inclusion of speed variable [15]. Therefore, the control of IMs presents noteworthy challenges due to this highly nonlinear and appended fifth order dynamics of the system under strong parameter and model uncertainties, and with only three state variables (i_{sd}, i_{sq} and ω_r) that are available for measurement. This is the one of the reasons why high performance control and estimation techniques of IMs have been receiving a lot of attention in the literature.

3. Variable frequency drives

With the advancement of AC drive technology, the VFDs are able to provide smoother speed tuning, greater motor control, and fewer energy losses. Based on the torque and speed control techniques, the IM-VFDs can be classified into two main categories namely the scalar and vector control methods, as illustrated in Fig. 2. A brief discussion on these control methods are given as follows.

3.1. Scalar control

Scalar control is a simple control technique used to control the speed of complex and nonlinear behavior of the IMs based only on magnitude and frequency of the applied voltages. The control is developed based on a per phase steady-state equivalent circuit of the IM with an objective of maintaining the magnetizing current constant by changing the magnitude of applied voltage proportional to the applied frequency. The magnitude and frequency needed to maintain this constant magnetizing current is then synthesized using a voltage source inverter. An example of a scalar control of IM which is based on a constant ratio of applied voltage to the frequency, widely known as the constant volts per hertz (or constant *V*/*f*), is shown in Fig. 3. For this particular example of control scheme, the speed is controlled in a closed loop manner by measuring the actual speed using a speed sensor. As shown in the figure, the difference between the reference rotor speed value, ${\omega_r}^r$, and the actual rotor speed, ω_r, which is speed error, is tuned via the conventional proportional-integral (PI) controller, and a limiter to obtain the slip-speed reference ${\omega_{sl}}^r$. Then, the slip-speed reference and electrical rotor speed are added together to generate the fundamental stator frequency reference. Thereafter, the fundamental stator frequency reference determines the amplitude of the

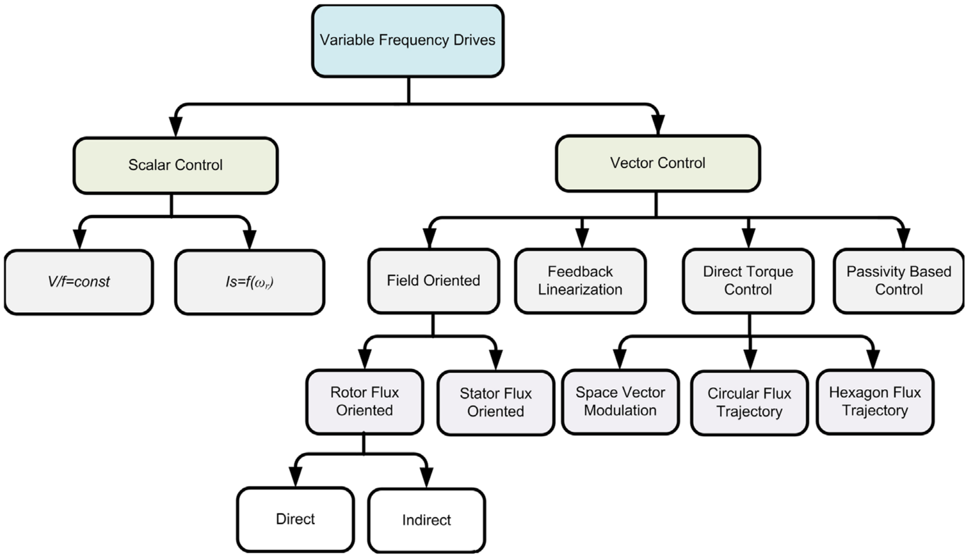

Fig. 2. Classification of variable frequency drives for IM control [16].

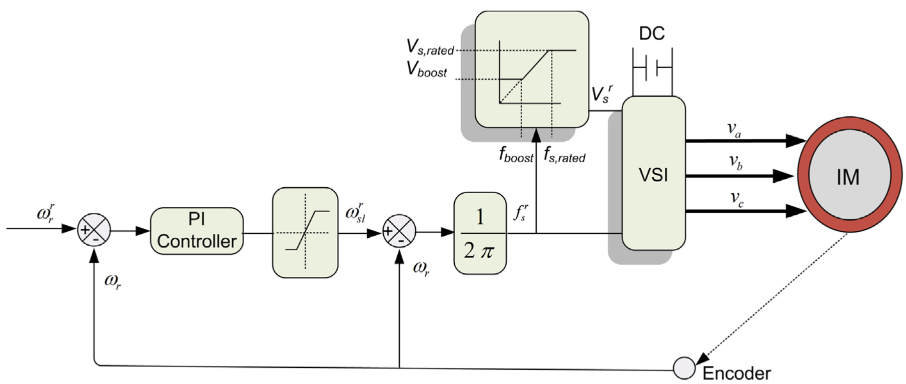

Fig. 3. Closed loop IM with constant V/Hz variable frequency drive.

fundamental stator voltage reference, V_s^r. Without the speed feedback (i.e. open loop constant *V*/*f*), the speed regulation will be poor and heavily depends on the mechanical load; nonetheless, for some non-critical applications this is good enough. The inclusion of the speed sensor will increase overall cost of the drive system, but yet the system is still not suitable to be used for applications where precise torque control is mandatory; scalar control is incapable of controlling the most essential variables in IMs, i.e. torque and flux [17]. The main drawbacks of this technique are the unsatisfactory speed accuracy, especially at low speed region, and poor torque response. The reaction of the motor to the applied frequency and voltage governs motor flux and torque indirectly based on the steady-state model of the IM [16] which is not valid in transient state. Therefore, for applications requiring precise torque control, vector control schemes are normally adopted as discussed in the next section.

3.2. Field oriented control (FOC)

Field oriented control (FOC) or vector control (VC) was introduced by Hasse and Blaschke from Germany, in 1969 and 1971 respectively [16]. On the contrary to the scalar control, the development of FOC control scheme is based on dynamic model of the IM where the voltages, currents and fluxes are expressed in space vector forms as given by Eqs. (1)–(4). The representation of the motor's quantities using space vectors valid under both steady state and transient conditions hence with FOC, excellent transient response can be achieved. The rotor flux FOC scheme is based on the frame transformation of all quantities to a rotating frame fixed to the rotor flux. In this rotating rotor flux frame, all quantities rotating at synchronous speed will appear as DC quantities. If the flux is aligned to the *d* axis of this reference frame, it can be shown that the *d* and *q* components of the stator current represent the flux and torque component respectively. This means that utilizing FOC, the control of IM is transformed to a simple control scheme similar to the DC motor control where the torque and flux components are decoupled. The way the rotor flux position is obtained determines the type of FOC as either direct FOC or indirect FOC. In indirect FOC, the flux position is obtained by adding the slip position to the measured rotor position, whereas in direct FOC it is calculated (or can also be measured) based on the terminal variables and rotor speed. Fig. 4 shows the block diagram of a direct rotor flux FOC with speed loop. The rotor speed, which is obtained from the encoder, is used as the speed feedback and also more importantly is used by the observer to calculate the rotor flux position. Alternatively, instead of rotor flux orientation, it is also possible to perform the orientation to the stator flux—which is known as stator flux FOC. It can be seen that in FOC scheme, the knowledge of rotor position need to be acquired accurately in order to perform the frame transformation. Inaccurate

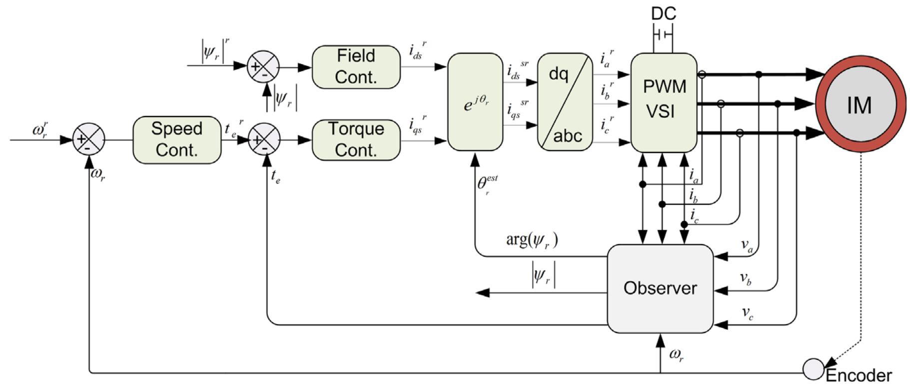

Fig. 4. Fundamental direct FOC technique with an observer used for rotor flux estimation.

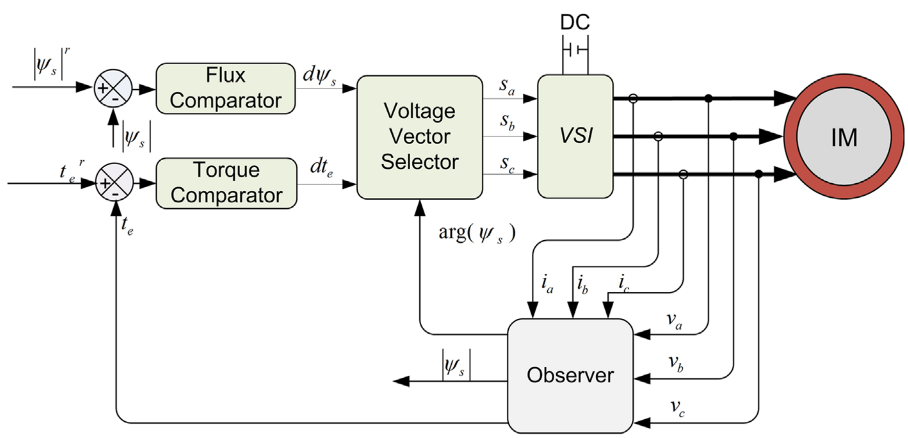

Fig. 5. Basic DTC scheme with an observer used for stator flux estimation.

rotor flux position causes the torque and flux not to be completely decoupled and consequently resulted in deterioration in the torque dynamics [18].

3.3. Direct torque control (DTC)

DTC has become significantly popular and can be considered as an alternative controller to the well-known FOC scheme due to its excellent torque response and its simple control algorithm [19,20]. The basic structure of DTC of IM scheme is shown in Fig. 5. The DTC scheme, as initially proposed in [19], consists of a pair of hysteresis comparators, torque and flux calculator, a lookup table, and a voltage-source inverter. The control structure of DTC is much simpler than the FOC system due to the absence of frame transformer, pulse width modulator, and a position encoder. The decouple control of torque and flux is established by selecting appropriate voltage vectors to maintain the torque and flux errors within their hysteresis bands [19]. In DTC, the accuracy of the estimated stator flux is important to ensure correct voltage vector selected for a decoupled torque and flux control. In its basic configuration, DTC scheme does not require rotor speed information since the estimation of stator flux is performed using voltage-model based observer. However, in order to improve the stator flux estimation at low speed, current-model based observer is normally used, which inevitably require the rotor speed information. Even if stator flux estimation is performed totally based on voltage-model, the rotor speed is still needed for a speed control system. In other words, rotor speed is one of the important parameters that need to be either measured or estimated to ensure proper DTC scheme implementation. Two of the major issues which are normally addressed in DTC drives are the variation of the switching frequency of the inverter used in the DTC drives with operating conditions and the high torque ripple. It is well known that the source or root to the variable switching frequency problem is the use of hysteresis comparators, in particular, the torque hysteresis comparator [20]. To solve these problems, various implementation schemes are proposed. These include the use of predictive control scheme [21,22], space vector modulation (SVM) technique [23], artificial intelligence (AI) [24] and constant switching controller [20].

4. Sensorless control strategies

Based on the above discussions, regardless of the control strategies used, speed measurement is something essential for control algorithm and/or speed control in the IM drive. The motor speed can be measured using tachometer or optical encoder. However, mechanical speed sensors are associated with several disadvantages: the increased size and cost of the drive system, reduced reliability and robustness, and regular maintenance of the speed sensor itself. Furthermore, in some applications, it is inappropriate to install the mechanical speed encoder at the motor shaft due to the physical and environment constraints. Accordingly, increasing attempts have been made to eliminate the encoder mounted at the motor shaft without affecting the performance of the VFD system. Hence, research interests on sensorless techniques applied to IMs have grown dramatically in the last few decades. Generally, the speed estimation techniques can be classified into two broad categories as shown in Fig. 1: estimation based on mathematical machine model and estimation through signal injection to exploit the anisotropy of the machine.

4.1. Model based estimation techniques

In model-based estimation techniques, Eqs. (1)–(4) of the IM are used to estimate the speed. The model-based estimation can be grouped into several techniques (see Fig. 1) which are discussed as follows.

4.1.1. Open loop speed estimation

It is possible to estimate the rotor speed directly from Eqs. (1) to (4) using the measured terminal quantities (voltage and current) provided that all parameters of the motor are known. Several techniques can be used to estimate the rotor speed as discussed in [18]. Most of the techniques of open loop speed estimator somehow involve integrations in order to obtain the stator flux and hence the rotor flux. The stator flux can be obtained by re-arranging Eq. (1) to obtain Eq. (6).

$$\psi_s = \int (v_s + R_s i_s)\, dt \tag{6}$$

Since integrators can easily saturate (in the presence of small DC offset in the measured currents), they are normally replaced with low-pass filters, which inevitably introduce magnitude and phase errors in the estimated stator flux, especially when the frequency is close to the cut-off frequency of low-pass filter. Avoiding the use of integrators obviously, will improve open-loop speed estimation especially at low speed where the back EMF is small. The open-loop speed estimators are also sensitive to variation in the motor parameters such as, stator and rotor resistances as well as rotor and stator-self inductances. The variation in the resistances is due to the temperature increase, whereas for the inductances, it is typically caused by the main flux saturation [18]. The performance of the speed estimators, and hence the drive system, degraded when these parameters varies from nominal values. The sensitivity to parameter variations can be reduced by employing closed-loop estimators or better known as closed-loop observers, such as Luenberger observer, model reference adaptive system (MRAS) and Extended Kalman Filter (EKF).

4.1.2. Model reference adaptive system

Typical speed estimation based on MRAS, as shown in Fig. 6, consists of reference and adjustable models, which have different structures and inputs, but estimate the same state variable ‘s’. The difference or error between the two estimates is fed to the speed adaptive scheme, which output (speed) is used to correct the adjustable model. Ideally, the estimated speed equals the actual speed when the error is minimized. MRAS observers, developed so far in the literature, are based on rotor flux, back EMF, and reactive power as the speed tuning signal [25–27]. When the rotor flux is used as the state variables to obtain the speed tuning signal, as stated earlier, a pure integrator used to estimate the stator flux (which is then used to obtain the rotor flux) is typically replaced with a low pass filter. As such, the performance of the estimator degraded below 2 or 3 times the cut-off frequency of the low pass filter [28]. Attempts have been made to correct the phase and magnitude errors due to the low-pass filters. Karanayil et al. [28] propose a small-time-constant cascaded LPFs to reduce the DC offset decay time.

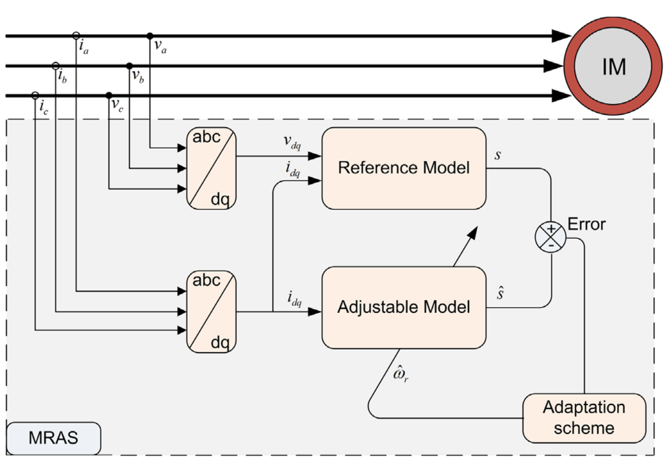

Fig. 6. Model reference adaptive system for speed estimation.

Other researchers have attempted to replace the voltage model (VM) in the reference model [10,29,30]. Authors in [10,29] replace the classical voltage model with neural network as a rotor flux observer. Sustainable zero speed in the steady state with zero load holding to 32 s was achieved in [10]. Alternatively one could use the back EMF [26,31] for signal tuning thus avoiding the use of integrators. In [30], a reference model, with the measured stator current of the IM, is compared with the estimated stator current using the stator voltage–current adjustable model. The current error is corrected using the estimated rotor speed calculated by an adjustment mechanism. Another study by Ravi Teja et al. [32] address a new MRAS based on instantaneous values of the product of voltage and current for stability enhancement of the driving system. Some other approaches based on artificial intelligence, to achieve an improved performance of the MRAS, are also proposed in the literature [25,29,30,33,34]. Among these studies, [35] introduce a hybrid of a fuzzy logic and sliding mode controller to replace the fixed-gain PI controller. This combined and more complex MRAS-based estimation is developed and claimed to give better performance with the minimum speed range of 30–100 rpm. However, owing to the noise in the measurements and non-linearity of the power converters, this technique failed to perform satisfactorily for sustained zero speed.

4.1.3. Full order and reduced order closed loop observers

To obtain robust speed estimation against parameter mismatch especially at low speed operations, several variations of closed loop observers have been developed [36–40]. An example of a full order observer or adaptive observer as proposed in [39] is shown in Fig. 7. For this proposed observer, the state variables (*d–q* stator-current and *d–q* rotor-flux) are represented by the vector ‘*x*’. Matrix ‘*A*’ contains the motor parameters and rotor speed. Since the speed is estimated, as seen in Fig. 7, the observer model, which estimates the stator current and rotor flux, is given by the following relation:

$$\frac{d}{dt}\hat{x} = \hat{A}\hat{x} + Bv_s + G(\hat{i}_s - i_s) \tag{7}$$

The symbol ‘^’ indicate an estimated values. In this scheme, the torque error, which is the cross product of the estimated rotor flux and the current error (i.e. $\hat{\psi}_r \times e_i$), is used to adjust the speed in the observer using an adaptation scheme, which is typically a PID controller. The observer gain matrix ‘*G*’, is chosen such that the eigenvalues of the observer are proportional to the eigenvalues of the machine, to ensure stable operation under normal operating condition [39]. Among recent studies, that help in the improvement of this estimation approach, Cirrincione et al. [36] propose an adaptive speed observer with a combination of a total least-squares neuron and the Luenberger observer. In this scheme, estimation of rotor speed at zero speed region is claimed with online tuning of stator and rotor resistances. Moreover, Davari et al. [37] propose a predictive model using sliding mode feedbacks. Two kinds of observers, reduced order observer and sliding mode full order observer (SMFOO), are combined with this prediction model. It is claimed that combination of the proposed prediction model and SMFOO results in stability in very low-speed region without parameter adaptation. Lastly, Salmasi and Najafabadi

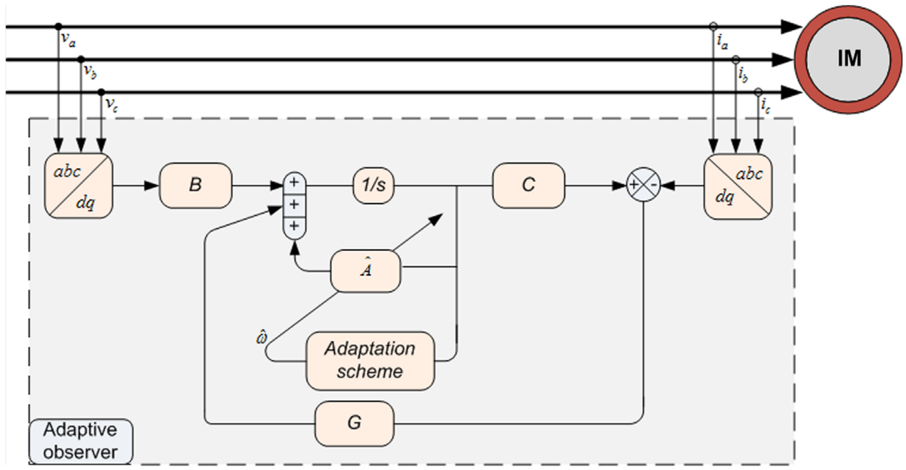

Fig. 7. Adaptive observer for speed estimation.

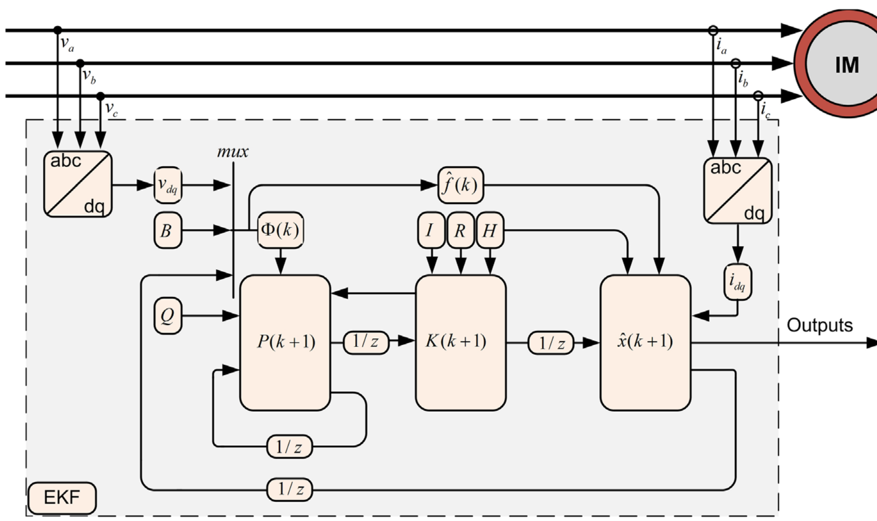

Fig. 8. Structure of Extended Kalman Filter.

[40] describe an adaptive observer capable of concurrent estimation of stator currents and rotor fluxes with online adaptation of rotor and stator resistances with using a single stator current and rotor speed.

4.1.4. *Extended Kalman Filter*

Besides the aforementioned deterministic schemes for the design of closed-loop observers, there are also stochastic approaches using Extended Kalman Filter (EKF) in estimating the speed of IMs. The Kalman Filter (KF) is a well established stochastic technique used in estimation problems. The stochastic method includes random disturbances, modeling errors, computational inaccuracies, and measurement errors of the system in solving the estimation problem. The KF is capable of estimating the nonmeasured parts of a linear dynamic system. This can be done by achieving a minimum covariance error that will lead to optimal estimated states. For nonlinear problems, such as the case of IMs, the EKF is strictly applicable. The non-linearity can be overcome by performing the linearization about the recent estimated states. The process requires a discrete model of the IMs, which can be given in the following general form:

$$\dot{x}(k+1)=f(x(k),u(k))+w(k) \tag{8}$$

$$f(x(k),u(k))=A(x(k))x(k)+Bu(k) \tag{9}$$

$$Y(k)=Hx(k)+v(k) \tag{10}$$

The variables f, Y, H represent the nonlinear function of the state variables and input values, the output state vector, and the measurement matrix, respectively. The system and measurement noises are represented by the white Gaussian noises w and v. The detailed matrix representation for (9) can be achieved by transforming Eq. (5) to a discrete form.

The following relation presents the linearization step which is performed around the recent estimated state vector $\hat{x}_i$ as given by

$$F_i(k)=\frac{\partial f_i(x_i(k),u(k))}{\partial x_i(k)}\bigg|_{\hat{x}_i(k)} \tag{11}$$

The recursive EKF algorithm can be written in the following relations:

$$P(k)=F(k)P(k)F(k)^{-1}+Q \tag{12}$$

$$K(k+1)=H^TP(k)(HP(k)H^T+R)^{-1} \tag{13}$$

$$\hat{x}(k+1)=\hat{f}(x(k),u(k))+K(k)(Y(k)-H\hat{x}(k)) \tag{14}$$

$$P(k+1)=(I-K(k+1)H)P(k) \tag{15}$$

The covariance matrices P, Q, and R represent the state estimation error, system noise, and output or measurement noise, respectively. The EKF algorithm goes through two main stages: prediction and filtering. The prediction stage is aimed to obtain the

next predicted states $\hat{f}(\cdot)$ and predicted state-error covariance matrix $\hat{P}(\cdot)$, while the estimated states $\hat{x}(k+1)$ are calculated by adding the predicted states and correction term (second term in Eq. (14)) in the filtering stage. The structure of the EKF scheme is shown in Fig. 8.

With EKF, it is feasible to estimate the unknown parameters of IM in a relatively short time, taking into account the system and measurement noises [41]. Due to the powerful and faster digital signal processors (DSPs) that are available nowadays, the problem of computational burden that is normally associated with EKF implementation is no longer the main issue. However, the performance of EKF-based estimation depends on the right selection of the filter matrices. Recently, several evolutionary and stochastic optimization methods have been proposed in the literature for tuning filter parameters; such as Simulated Annealing (SA) [42] and Particle Swarm Optimization (PSO) [43], which contribute satisfactorily on the performance of the EKF achieving sufficient results for a wide speed range. Nevertheless, trial and error methods are still mostly in use. Differently, Barut et al. [41] propose a so-called braided-EKF (switching between two models: stator resistance and rotor resistance models) to simultaneously estimate eight parameters which are *d–q* current, *d–q* flux, rotor speed (with the use of equation of motion), stator and rotor resistances, and the load torque. Good results in real-time implementation over a wide speed range are achieved. In addition, low speed results at less than 3 rpm are reported. In an attempt to solve the problem of switching between models in EKF, Ozsoy et al. [44] estimate all these eight parameters using an 8th order EKF. Nevertheless, this approach fails to be superior to the braided-EKF as the performance of EKF deteriorates when a high number of states are estimated with a limited number of inputs. Among other studies to improve on the performance of the EKF, Gherram et al. [45] use artificial neural networks (ANNs) based on EKF for mutual inductance, rotor resistance, and rotor speed estimation of an IM for solving the problem of covariance matrices. The results are said to be more efficient than those obtained with conventional EKF. In addition, Danan et al. [46] use EKF based on Γ^{-1} model for sensorless rotor FOC to simplify the state matrix and reduce computation of EKF. Nonetheless, assumption of the white Gaussian noise and lack of analytical approaches for selection covariance matrices are some of the limitations in the conventional EKF [11].

4.1.5. Sliding mode observer

The SMO is featured as an effective estimator due to the following advantages: simplicity, easy implementation, robustness to parameter variations, less restrictive design, and no extensive computations [47]. The block diagram of the sliding mode observer is shown in Fig. 9. The current error, which is the difference between the actual and the estimated currents, is used to define a sliding hyperplane surface. It is forced to zero by the switching action of the controller. The control law is designed so that states move toward the surface in a finite time. Then, the SMO forces the states to remain within control structure boundaries and slide toward the desired position [5,37,47–53].

Chattering is the common problem of the sliding mode scheme due to high frequency control in practical applications. Thus, to reduce the problem of chattering and to improve the performance of the sliding mode, several studies have been addressed in the literature. Among recent modifications related to the SMO for the sensorless IM drives, Comanescu et al. [48] present an Integral Sliding-Mode Current Control (ISM-CC) scheme. This ISM-CC scheme regulates and decouples the synchronous *d–q* currents. The proposed speed estimation scheme shows a good dynamic performance for the system in the steady state mode. A sliding-mode current and flux observer using a continuous approach is addressed to estimate the speed and rotor resistance which showed a good performance in the field oriented controlled system [49]. Other estimation techniques [53,54], based on SMO using Popov's hyper-stability theory, are described to estimate the rotor speed and stator resistance. Satisfactory results are presented over different speed regions. Lascu et al. [47] combine SMO with DTC in their proposed sensorless induction motor drive without the need for speed adaptation achieving good results with full load in very low speed region (3 rpm). An artificial-intelligence-based study using fuzzy logic and SMO is proposed in [52] to help on speed estimation. Although it is claimed that satisfactory dynamic performance over a wide speed range is achieved, this method requires complex algorithms or fuzzy rules which are constructed by a time-consuming procedure.

4.1.6. Other estimation schemes

Other techniques associated with sensorless induction motor drives are proposed in [55–58], for parameter adaptations and improvement of speed at low range. An enhanced open-loop speed estimation scheme for affordable sensorless motor drives is presented in [55] whereby the focus is given to the main problem of open-loop based estimator, which is sensitive to parameter variations. Boussak and Jarray [56] proposed an indirect stator-flux-oriented control (ISFOC) scheme based on measurement of stator currents for speed and stator resistance estimations. The proposed method shows satisfactory results at low speed operation with stator resistance tuning. Santana et al. [57] develop a model-based predictive control (MBPC), combined with EKF for

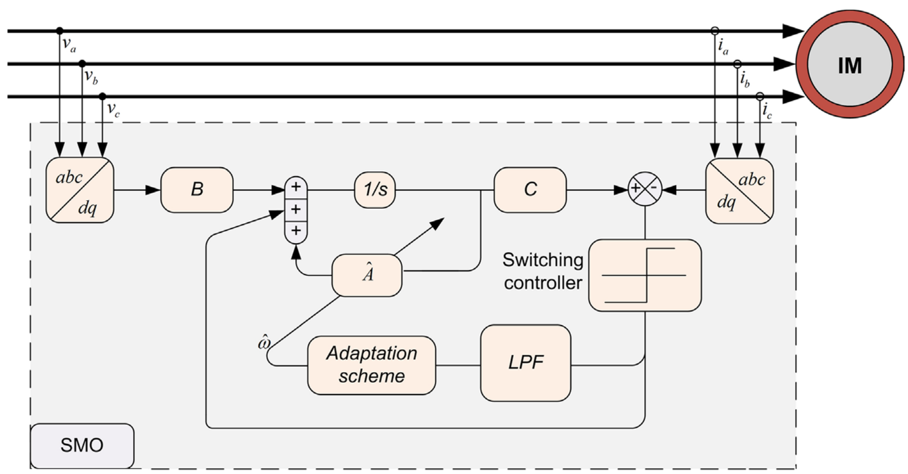

Fig. 9. Sliding mode observer for speed estimation.

estimating the rotor speed and rotor flux. As a result, the speed and the rotor flux can be controlled without the need of current regulators. Toliyat et al. [58] use artificial neural networks (ANNs) in closed loop observers for estimating mutual inductance and rotor resistance of induction motors. The proposed ANNs are used to develop an associated scheme for storing the calculated values and for calculating these values during the transients.

4.1.7. Difficulties in model based estimation

Model-based IM speed estimation has been applied for the past several decades. As discussed in the previous sections, various techniques have been proposed and all of them are based on the dynamic induction machine equations given by Eqs. (1)–(4). The problems associated with the model-based estimation techniques become apparent particularly at low frequency and zero speed operations. In fact, the method completely failed at zero frequency [9,11]. At low frequency, the signal-to-noise-ratio (SNR) is poor due to the low stator voltage. On top of that, non-linearity in the PWM inverters caused by the blanking time and devices forward voltage drop further contribute to the problem. The situation becomes worst when there are parameter mismatch between the actual machine parameters and the ones that are used by the controllers. The main source of problems associated with a model-based estimation can be summarized as follows:

(1) Signal acquisition errors: Terminal variables are measured using sensors which are then processed by the DSP to estimate the torque, flux and speed. The measured signals will inevitably contain noises and the sensors themselves will typically introduce DC offset values that can saturate the integrators employed in the estimations. The low voltage at low frequency translates to a poor SNR and hence further aggravates the problem.
(2) Inverter non-linearity: The inverter causes nonlinear dead-time effects which require compensation at low speed for good dynamic performance. Another source of nonlinearities is owing to supply voltage drops. These two non-linearity characteristics of the inverters can become significant at low frequency where the magnitude of the voltage is small. Moreover, additional effect, which results from the dead time compensation sensitivity to the current reversal point, also has to be considered. Due to these non-linearity characteristics, the calculation of the stator voltage vector from the PWM switching which assumed linear relation becomes inaccurate. Consequently, the stator voltage vector calculation that is used in the speed will introduce speed estimation error.
(3) Parameter mismatch: The parameters of the machines are normally extracted during the commissioning, which can be obtained either manually or by using the inverter in self-commissioning process. The accuracy of the extracted parameters is extremely important to ensure excellent drive performance as well as accurate speed estimation. Unavoidably, these parameters will vary with operating conditions and temperature. In particular, the rotor and stator resistances which are used extensively in the estimations increase with temperature. On the other hand, the stator and rotor inductances will vary from their nominal assumed values because of the magnetic saturation. The mismatch in parameters resulted in the inaccuracies in the estimated quantities; in fact can even cause instability to the drive system. As mentioned earlier, the effect of motor parameters mismatch on the rotor speed estimation becomes worst at low speed operation.

4.2. Estimation through signal injection and parasitic effects

Due to the problems of parameter variations and unobservable rotor speed at zero stator frequency in sensorless drives based on fundamental machine equations, a relatively new approach based on signal injection (SI) has gained popularity. In this approach, the induction motor is injected with extra, low level signals usually at high frequency [11]. The speed or rotor position information is then extracted from the measured current or voltage by exploiting the anisotropy of the machines. There are trade-offs in selecting the magnitude and frequency of the injected carrier signals [59]. If the magnitude of the injected signal is large, this would increase the torque ripples and deteriorate the IM control system, whereas a carrier signal with a small magnitude would create a small SNR. Similarly, if a small carrier frequency is used, it would be difficult to separate carrier signals from the fundamental frequency signals. Therefore, the magnitude and frequency of the carrier signals should be selected, so that the performances of the speed processing/tracking technique and the motor control system are optimized.

Different forms of signals (i.e. periodic, alternating) are injected in a particular spatial direction to IM [13]. These injected signals are initially modulated by the orientations of the motor asymmetries, and are then demodulated to extract the required information. Two classifications of signals are produced that are used for estimating the rotor speed: negative-sequence carrier-signal and zero-sequence carrier-signal components [12]. Signal processing can be difficult due to required frequency tracking, low spectral separation and poor SNR which can be overcome with modern signal processing techniques [13,60]. The general block diagram of this technique, applied to FOC drives, is shown in Fig. 10. The various methods based on machine saliencies are summarized as follows.

4.2.1. Rotor slot tracking

With this method, changes in reactance caused by rotor slots are detected from the stator currents or back EMF of the machines. Various methods have been introduced recently to extract this signal. McNamara et al. [61] propose an adaptive frequency-tracking algorithm for a real-time speed estimation. This proposed scheme can offer accurate real-time speed estimation during the fluctuations of frequency and mechanical load. Keysan and Ertan [62] use a rotor slot harmonics detection technique with short computation time. Staines et al. [63] introduce rotor-position estimation at zero and low frequency using rotor slotting and zero-sequence current which achieve good results in a 0–10 rpm range. Zhi et al. [64] address a sensorless rotor temperature estimator through the current harmonic spectral estimation. This proposed scheme is claimed to provide information on rotor speed, inductance, a rotor resistance and a rotor temperature without the need for motor parameters.

4.2.2. Custom designed or modified rotor slots

This method uses specially built or modified machines to produce a spatially modulating leakage reactance over each pole pitch. This is done by spatially modulating the width of the rotor

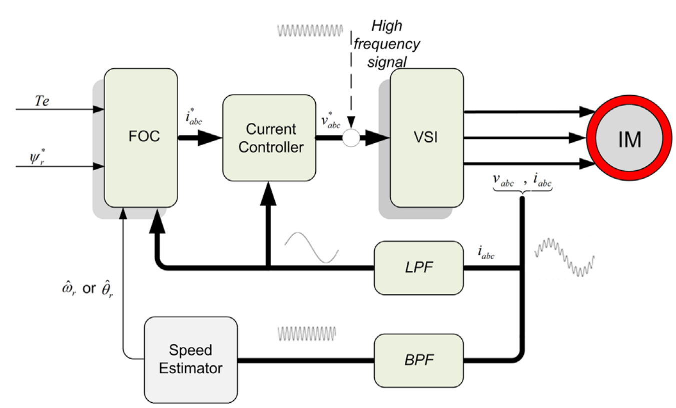

Fig. 10. FOC drive with speed estimation based on parasitic effects.

slots or the slot fill height smoothly over each pole [65,66]. In order to obtain the information of the rotor position from this spatially modulating leakage reactance, a high frequency signal is injected to the stator circuit. Since at high frequency the impedance of the equivalent circuit of the induction machine is dominated by the leakage inductances, the amplitude of the high frequency stator current will be modulated proportionally with rotor position. The rotor position information contained within a large fundamental signal, therefore, extracting it is not an easy task [67]. At high speeds, when high voltage is applied to the machine, large signal has to be injected which can cause extra losses. Further, this technique has to use customized or modified machines.

4.2.3. Saturation caused by main flux

The magnetic flux saturation in the main flux path causes a modulation in the leakage path of the IM [9]. The amount of modulation however depends on the level of the main flux of the machine. In FOC drives, this effect will result in a difference between the d and q axis leakage reactances in the rotating reference frame. In [68], the position of the rotor flux in FOC drive is tracked by injecting a high frequency signal to the estimated d axis of the flux. The position of the rotor flux is obtained from the measured impedance difference. However, the rotor speed or position (if required) has to be calculated from the obtained rotor flux position [69].

5. Conclusion

Induction motor drives are known to have significantly contributed to the world energy consumption. Consequently, considerable worldwide energy savings can be achieved if VFDs are used to replace most of the existing non-adjustable or single-speed IM drive systems. For high performance IM drive and speed control purposes, rotor speed information is mandatory and thus require speed sensor to be installed. Clearly, IM drives without mechanical speed sensors at the motor shaft are more attractive due to their lower cost and higher reliability.

In this paper, several techniques of speed estimation for sensorless controlled IM drives are reviewed. Types of VFDs applied to IMs are summarized. Recent studies on the various speed estimation techniques with wide speed range of operations including low and zero speed for IM motor drives are briefly described.

Model-based techniques give very good results for medium and high speeds while SI approaches are reported to work best for low and sustainable zero speed regions. Combination of both methods can lead to an excellent performance for the sensorless IM-VFDs over a wide speed range. Thus, well-established energy-conserving drive system is achieved for improving the dynamic performance and economical feature of IMs.

Acknowledgments

The authors would like to thank the Universiti Teknologi Malaysia (UTM) and the Ministry of Science, Technology and Innovation (MOSTI) of the Malaysian government for providing the funding for this research.

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